

In the Claims

Claims 1 – 3 (Cancelled)

4. (Currently Amended) The method according to claim [3] 16 in which the prediction models are formed by neural networks or other models for estimating functions that are each characteristic of a mode s and compete for description of the individual elements of the time series according to predetermined training rules.

5. (Currently Amended) The method according to ~~one of the claims 1 through 4~~ claim 16 in which the series of mixed system modes g_i is determined from the prediction models f_{ij} and interpolation parameters a, b according to $g_i = a(s)f_{i(s)}(x) + b(s)f_{j(s)}(x)$.

6. (Previously Presented) The method according to claim 5 in which the interpolation parameters are selected according to $0 < a(s) < 1$ and $b(s) = 1 - a(s)$.

7. (Currently Amended) The method according to claim 6 in which the values $a(s)$ are restricted to a certain resolution figure R ~~and/or are equidistant~~.

8. (Currently Amended) The method according to claim [1] 16 in which the series of mixed prediction models g_i is detected by determining a prediction for each time increment with each of the possible prediction models, resulting in a time-dependent prediction matrix from which a mean prediction error for randomly selected segmentations can be derived, whereby the sought series of mixed prediction models g_i is the segmentation with the smallest prediction error or the maximum probability.

9. (Previously Presented) The method according to claim 8 in which the search for the segmentation with the smallest prediction error is made by a dynamic programming technique that is equivalent to the Viterbi algorithm for hidden Markov models, whereby an optimum sequence of

prediction models is determined using a minimized cost function C^* of the prediction and the segmentation is derived inductively from the sequence of prediction models.

10. (Currently Amended) The method according to claim [1] 16 in which drift segmentation is followed by an additional step to reduce the number of prediction models used for modeling where the number of prediction models is reduced sequentially, associated with a determination of the mean prediction error, until a further reduction of the number of prediction models means an increase in the prediction error.

11. (Currently Amended) The method according to claim [1] 16 in which the time series of at least one of the system variables $x(t)$ comprises a time series of physiological parameters described by the Mackey-Glass delay differential equation $dx(t)/dt = -0.1x(t) + 0.2x(t - t_d) / (1 + x(t - t_d))^{10}$.

12. (Currently Amended) The method according to claim [1] 16 in which the time series of at least one of the system variables $x(t)$ comprises a time series of physiological parameters that are characteristic of the development of sleep and wake modes.

13. (Previously Presented) The method according to claim 12 in which the physiological parameters comprise EEG signals.

14. (Currently Amended) The method according to claim [1] 16 in which the time series of at least one of the system variables $x(t)$ comprises a time series of speech signals.

15. (Cancelled)

16. (New) A method for detecting modes of a dynamic system with a multiplicity of modes s_i that each have a set $\alpha(t)$ of characteristic system parameters, said method being performed with a computer and comprising the steps of:

performing a switch segmentation of a time series of at least one system variable $x(t)$,
in which the switch segmentation is a simulation of a training time series of the system or of
the time series to be investigated with several, competing prediction models,

detecting predetermined prediction models f_i for system modes s_i for each system
variable $x(t)$ in each time segment of a predetermined minimum length,

performing a drift segmentation subsequent to said switch segmentation in which, in
each time segment in which there is a transition of the system from a first system mode s_i to a
second system mode s_j , a series of mixed prediction models g_i is detected and produced by
linear, paired superimposition of prediction models $f_{i,j}$ of the two system modes $s_{i,j}$, and

performing a prediction of a state of said dynamic system directly following to a
current state, said prediction being based on the detected current modes.

17. (New) A method for detecting modes of a dynamic system with a multiplicity of
modes s_i that each have a set $\alpha(t)$ of characteristic system parameters, said method being performed
with a computer and comprising the steps of:

performing a switch segmentation of a time series of at least one system variable $x(t)$,
in which the switch segmentation is a simulation of a training time series of the system or of
the time series to be investigated with several, competing prediction models,

detecting predetermined prediction models f_i for system modes s_i for each system
variable $x(t)$ in each time segment of a predetermined minimum length,

performing a drift segmentation subsequent to said switch segmentation in which, in
each time segment in which there is a transition of the system from a first system mode s_i to a
second system mode s_j , a series of mixed prediction models g_i is detected and produced by
linear, paired superimposition of prediction models $f_{i,j}$ of the two systems modes $s_{i,j}$, and

performing a control of said dynamic system, including determining a deviation of a current state of said dynamic system from a setpoint state and deriving an appropriate control strategy on the basis of said deviation.

18. (New) The method according to claim 6 in which the values $a(s)$ are equidistant.

19. (New) The method according to claim 17 in which the prediction models are formed by neural networks or other models for estimating functions that are each characteristic of a mode s and compete for description of the individual elements of the time series according to predetermined training rules.

20. (New) The method according to claim 17 in which the series of mixed system modes g_i is determined from the prediction models f_{ij} and interpolation parameters a, b according to $g_i = a(s)f_{i(s)}(x) + b(s)f_{j(s)}(x)$.

21. (New) The method according to claim 20 in which the interpolation parameters are selected according to $0 < a(s) < 1$ and $b(s) = 1 - a(s)$.

22. (New) The method according to claim 21 in which the values $a(s)$ are restricted to a certain resolution figure R .

23. (New) The method according to claim 17 in which the series of mixed prediction models g_i is detected by determining a prediction for each time increment with each of the possible prediction models, resulting in a time-dependent prediction matrix from which a mean prediction error for randomly selected segmentations can be derived, whereby the sought series of mixed prediction models g_i is the segmentation with the smallest prediction error or the maximum probability.

24. (New) The method according to claim 23 in which the search for the segmentation with the smallest prediction error is made by a dynamic programming technique that is equivalent to

the Viterbi algorithm for hidden Markov models, whereby an optimum sequence of prediction models is determined using a minimized cost function C^* of the prediction and the segmentation is derived inductively from the sequence of prediction models.

25. (New) The method according to claim 17 in which drift segmentation is followed by an additional step to reduce the number of prediction models used for modeling where the number of prediction models is reduced sequentially, associated with a determination of the mean prediction error, until a further reduction of the number of prediction models means an increase in the prediction error.

26. (New) The method according to claim 17 in which the time series of at least one of the system variables $x(t)$ comprises a time series of physiological parameters described by the Mackey-Glass delay differential equation $dx(t) / dt = -0.1x(t) + 0.2x(t - t_d) / 1 + x(t - t_d)^{10}$.

27. (New) The method according to claim 17 in which the time series of at least one of the system variables $x(t)$ comprises a time series of physiological parameters that are characteristic of the development of sleep and wake modes.

28. (New) The method according to claim 27 in which the physiological parameters comprise EEG signals.

29. (New) The method according to claim 17 in which the time series of at least one of the system variables $x(t)$ comprises a time series of speech signals.

30. (New) The method according to claim 21 in which the values $a(s)$ are equidistant.